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Modeling the climate suitability of tea [*Camellia sinensis*(L.) O. Kuntze] in Sri Lanka in response to current and future climate change scenarios

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ABSTRACT

Knowledge of potential distributions and habitat preferences of tea (Camellia sinensis) under current and future climate conditions are vital for policy makers and stakeholders to develop suitable adaptation measures to mitigate against any detrimental effects of climate change. Without broad awareness of climate suitability and potential changes in distributions of tea growing areas, efforts of expanding the productivity of tea would remain ineffective. This study aimed to model the climate suitability of tea in Sri Lanka in response to the current and future climate change scenarios using the correlative habitat suitability model MaxEnt. Three representative concentration pathways were used under MIROC5 and CCSM4 global climate models for the year 2050 and 2070. The MaxEnt model projected current habitat suitability for tea based on existing datasets with a mean AUC of 0.92. The TSS value with a mean 0.847 ± 0.007 signifies high accuracy of predicting suitability habitats while the maximum kappa value (k) of the current and future models was around 0.454, indicating the overall performance of the model was good. In relation to the current time, areas of 6090 km^2 (9.3%), 5769 km^2(8.8%), and 5086 km^2 were projected as potential areas of having optimal, medium, and marginal climate suitability for tea, respectively. Results show that most of the optimal and medium suitability areas in the low elevation areas would be lost to a greater extent in comparison to the high elevation areas for all tested RCPs by 2050 and 2070 under both GCMs of MIROC5 and CCSM4. The comparison of the current and future distributions of suitable tea growing areas revealed a decline of approximately 10.5%, 17% and 8% in total 'optimal', 'medium', and 'marginal' suitability areas respectively, implying that climate would have a negative effect on the habitat suitability of tea in Sri Lanka by 2050 and 2070.

1. Introduction

Tea [*Camellia sinensis*(L.) O. Kuntze] is a prominent cash crop in the world, and it is the world's most extensively consumed health beverage after water (Gramza-Michałowska, 2014; Khan and Mukhtar, 2013; Vernarelli and Lambert, 2013) because of its well-known antioxidants, flavonoids and medicinal properties (de Godoy et al., 2013; Gramza-Michałowska, 2014). Tea is a perennial evergreen shrub that is commercially grown in many parts of the world; the four biggest tea-producing nations are China, India, Kenya and Sri Lanka (FAO, 2013). The global tea consumption demand exceeds production and is growing at a rate of approximately 5% per year, with a rising demand for black tea and reduced global production of black tea by 2.48% from 2006 to 2016 (FAO, 2015).

Ceylon tea is repeatedly praised as "the highest-quality tea in the world" as it contains unique aroma and taste characteristics (Hicks, 2009). Tea is grown on more than 203,020 hectares across the island, and the cultivation areas are broadly divided into low-grown (< 600 m a.s.l), mid-grown (600–1200 m a.s.l) and high-grown (> 1200 m a.s.l) areas, depending on the elevation (Bandara, 2012). The types of tea are further divided into seven main growing regions: Ruhuna and Sabaragamuwa in the low-grown area; Kandy in the mid-grown; and Nuwara Eliya, Dimbula, Uva and Uda Pussallawa in high-grown area of Sri Lanka (See Fig. 1) (Rajapaksha et al., 2017).

As a major plantation crop in Sri Lanka, tea plays an important role in the economy, contributing 1.1% of the Gross Domestic Production (GDP), while accounting for 15% of the net foreign exchange earnings (Esham and Garforth, 2013). The total production of Sri Lanka-made tea was recorded as 338 million kg in 2014, which accounted for 18.3% of tea exports globally (Jahfer and Inoue, 2014). Moreover, the tea sector generates substantial employment opportunities, with 2,200,000 people currently engaged in this field, which is approximately 10% of

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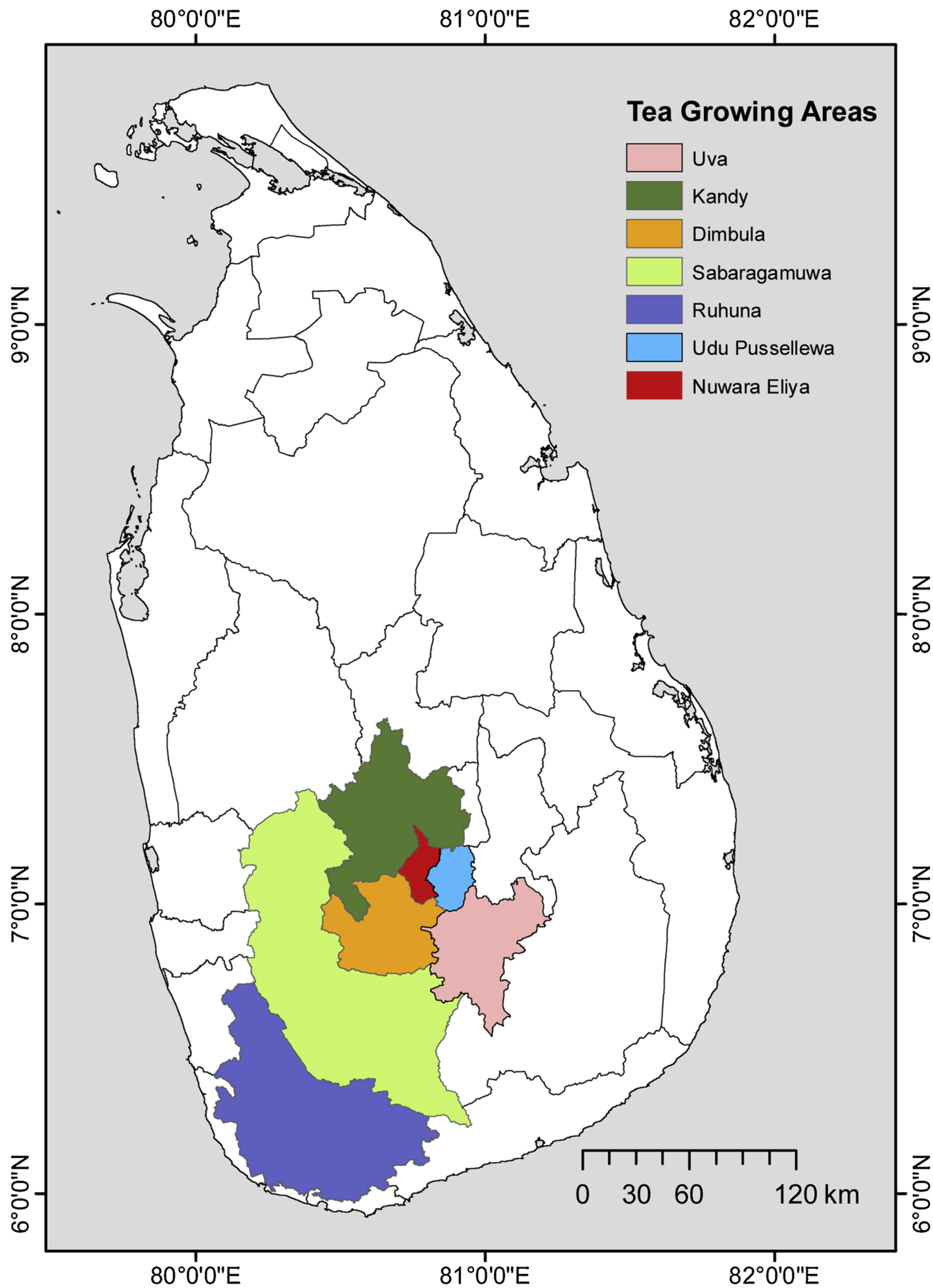

Fig. 1. Major tea growing areas in Sri Lanka.

the total population of Sri Lanka (Jahfer and Inoue, 2014; Perera, 2014). In addition to the economic benefits, the social and ecological significance of tea production is also substantial in the country, as it sustains ecological processes of carbon sequestration, soil fertility, and water conservation, while serving as the main beverage in social gatherings and cultural events (Ahmed et al., 2014; Li et al., 2011).

The Sri Lankan tea industry is currently confronted by a number of difficulties, such as resource constraints, competition for land, a stagnant area under tea, low productivity, lower replanting rate, higher cost of production and unavailability of adequate labor (Herath and Weersink, 2007). Additionally, other repercussions of climate change are crop-weed competition, the proliferation of pests and diseases, drought damage, soil losses and infertility in tea fields, thus increasing the cost of production and posing a threat to the tea industry (Gunathilaka et al., 2017). In addition to the above challenges, climate change has become a dominant topic for most of the major tea-producing countries, including Sri Lanka (FAO, 2014; Jayasuriya et al., 2011).

Notably, one of the pivotal interests of the Food and Agriculture Organization (FAO) has been assessing the effect of climate change on tea production (FAO, 2013; FAO, 2014). As a result, major tea producing countries such as Kenya are becoming less productive due to unreliable and undesirable rainfall, temperature and hail (FAO, 2014). Additionally, the Sri Lankan tea industry has become a victim of the consequences of global climate change, mainly due to the nature of its physiology and cultivation pattern (Wijeratne, 1996b; Wijeratne and Chandrapala, 2014). Therefore, a number of studies have determined that climate change negatively affects the quality and quantity of tea (Ahmed et al., 2014; Duncan et al., 2016; Dutta, 2014; Gunathilaka et al., 2017; Wijeratne, 1996c; Wijeratne et al., 2007).

Regarding climate change projections, Sri Lanka is predicted to face more incessant extreme weather events such as rising temperature and more severe rainfall (FAO, 2014). The functional quality of tea is influenced by climate change because concentrations of the methylxanthine caffeine and various polyphenolic catechin compounds are highly correlated with rainfall patterns (Ahmed et al., 2014). Trend analyses have shown that most tea-growing regions have received low-intensity rainfall during the past 20 years for all agroecological zones in Sri Lanka (FAO, 2014). Future climate projection estimates indicate that the increase in temperature by 2070 will be in the range of +0.4 °C to +3 °C per year, whereas rainfall is anticipated to increase with an uneven distribution pattern (Wijeratne et al., 2007). Under a medium global emission scenario, the mean temperature during the northeast and southwest monsoon seasons is predicted to increase by approximately 2.9 °C and 2.5 °C, respectively, by the year 2100 (Eriyagama and Smakhtin, 2010). More frequent and severe drought occurrences are also anticipated as a result of climate change (Pandey et al., 2003). The magnitude of these climate changes on tea cultivation will differ across the major tea-growing regions (i.e., low, high and mid-grown areas) (Wijeratne et al., 2007; Wijeratne and Chandrapala, 2014). Gunathilaka et al. (2017) estimated the relative impact of projected climate change under GCM model scenarios of A2, A1B, and B1 for three different time horizons (i.e., 2026–2035, 2046–2055, and 2081–2090) for low-, mid-, and high-grown tea estates. The predicted impacts of temperature and rainfall changes resulted in adverse implications on tea production in all tested elevations.

Furthermore, a 1 °C rise in mean temperature may create a 4.6% reduction in tea production, whereas an additional 100 mm of annual rainfall drops tea production by approximately 1% (Wijeratne et al., 2007). An optimum temperature for the shoot replacement cycle is considered as 22 °C, and if the temperature is not in the range of 18 and 25 °C, conditions are less favorable for tea shoot growth and development (Jayasinghe et al., 2018). Moreover, the predicted CO_2 level in the atmosphere will be in the range of 600–700 ppm by the year 2100. Yield projections for the year 2050 show that increasing temperatures may reduce tea yields in agroecological regions of up-country intermediate (IU), mid-country wet (WM) and low-country wet (WL), while increasing the yield in up-country wet (WU) region (Wijeratne et al., 2007). Furthermore, the predicted impact of climate change on tea production is expected to increase at high elevations, whereas it is likely to decrease at low elevations per the predictions made using the Sri Lanka Country Report on Climate Change, which is based on General Circulation Models (Wijeratne et al., 2007).

Adding to the above climatic constraints, another critical impact of climate change is the alteration of species distributions across the geographical area (Challinor et al., 2014; Wheeler and Von Braun, 2013). Brouder and Eriksson (2013) stated that the tea industry can be expanded by increasing the land area under tea cultivation, but suitable tea growing lands have been reduced by the effects of climate change. Tea cultivation in Sri Lanka diminished significantly from 1976 to 2013, whereas an increase of 126.2% occurred in areas under tea cultivation in Kenya over the same period, which results in a decreasing trend in Sri Lanka's share of world exports, while that of Kenya shows a significant increase (Thushara, 2015). In addition, degraded soil properties and old tea cultivation make tea lands highly vulnerable to the unfavorable effects of climate change (Wijeratne, 2012).

The areas suitable for tea cultivation in Sri Lanka may shift to other areas as tea cultivation are bound to specific ecophysiological requirements, and this suitability is likely to change with climate change. In addition, areas that are already struggling with the impacts of extreme climate events may diminish or lose tea growing capacity. Additionally, tea species can adapt to climate conditions, which may allow cultivation to both continue in existing areas and spread to new suitable areas, where these species can experiences desirable climatic conditions for sustaining their cultivation. To alleviate complications on the tea sector in Sri Lanka, novel strategies need to be formulated to battle extreme climatic scenarios to gain numerous benefits from this industry.

While the impact of climate change on tea quality and quantity has been widely studied(Ahmed et al., 2014; Duncan et al., 2016; Dutta, 2014; Gunathilaka et al., 2017; Wijeratne, 1996b; Wijeratne et al., 2007), no previous assessment of climate suitability for tea has been undertaken in Sri Lanka, and the country does not monitor the impact of climatic variation on tea cultivation distribution. Thus, we have little idea of the precise distribution pattern of tea cultivation in Sri Lanka under climate change, and it is important to understand potential changes in the distributions of tea to propose suitable adaptation measures to reduce any detrimental effects. Without a broad awareness of species habitat and distribution, efforts to expand the productivity of tea may remain inadequate and inefficient. Therefore, a timely task is to evaluate the relationship between the climatic requirement of tea species and its' current and future distribution patterns across the island.

Scientists from various countries are increasingly looking to model prognoses of species' distributions under climate change to form management strategies (Beaumont et al., 2017; Benito et al., 2009; Elith et al., 2010; Nazeri et al., 2015, 2012; Tsoar et al., 2007); however, suitability analysis for *Camellia sinensis* is very few in the literature compared to other perennial crops, except for those models developed to identify suitable tea growing areas in Malawi (Bartling et al., 2017), China (Brouder and Eriksson, 2013), Kenya (Leshamta, 2017), and Uganda (Muthee et al., 2019) and land suitability assessments in Assam and other areas of India (Adhikari et al., 2015). Climate suitability for tea would provide a comprehensive basis for land resource planning, and climate suitability approaches are usually applied to measure land use potential for certain crops under both current and future climatic scenarios at a regional scale (Brown et al., 2008; Pelizaro et al., 2011). Climate suitability evaluation approaches usually enumerate land potential for particular flora and fauna, and it predicts whether a certain region has increasing or decreasing suitability, indicating where shifts in cultivation zones can be considered as suitable adaptation remedies (Allbed et al., 2017; Beaumont et al., 2014; Da Silva et al., 2017; Kumar and Tehrany, 2017; Lamsal et al., 2018a, b; Paterson et al., 2017; Ramirez-Cabral et al., 2016; Shabani et al., 2016a, b; Shabani et al., 2018; Taylor and Kumar, 2012).

Species distribution modeling can be undertaken using a number of statistical approaches, such as logistic regression; boosted regression trees (BRT); multivariate regression splines; and using climate envelope models (CEMs), random forests (RF), and k-nearest neighbor (K-NN) (Elith et al., 2006). Maximum entropy (MaxEnt) is a high-performing species distribution modeling (SDM) method, which is known to be one of the most accurate models to predict species distribution using species occurrence and environmental data (Elith et al., 2006; Phillips et al., 2006). MaxEnt weights each environmental variable at present location and then makes predictions of particular species distribution in unsampled locations according to the algorithm written by Phillips et al. (2006).

The species distribution approaches can forecast whether some species are shifting their geographic ranges, contracting, expanding or fragmenting in response to global environmental change, or face extinction and distribution to other potential areas where they can sustain their life cycles under altered climates (Yu et al., 2011). As occurrence, distribution and the abundance of tea species can be altered by climate change, predicting the future reserve areas likely to be climatically suitable for tea is a crucially important factor for policymakers and stakeholders of the tea sector in Sri Lanka. A range of tea species distribution maps in Sri Lanka can be produced with this approach, and the potential exists to use it in decision-making to guide management and policy formation on climate change adaptation and mitigation in the tea sector that may reveal how the industry ought to adapt in the future.

A dire need exists for this information for making sound management decisions in tea plantations, and species distribution models are

currently the most promising tool used to form spatially explicit predictions of environmental suitability for species. The aim of this study therefore was to identify the suitable areas for tea cultivation in Sri Lanka based on bioclimatic and environmental characteristics in response to current and future climate change scenarios. Furthermore, this study was conducted to assess the climate suitability for tea cultivation in Sri Lanka using maximum entropy (MaxEnt) (Phillips et al., 2006) and to estimate potential tea distribution under the climate extremes in 2050 and 2070 under four different climate scenarios of the Fifth Assessment Report (AR5) from the Intergovernmental Panel on Climate Change (IPCC) for all tea growing areas of Sri Lanka.

2. Materials and methods

2.1. Study area

The study area covers the whole of Sri Lanka, which is geographically positioned in Universal Transverse Mercator (UTM) zone 44. The climate is characterized as tropical, hot and humid throughout the year, based on the location of Sri Lanka in the Asiatic monsoon region, lying between 5°55′ to 9°51′ North latitude and between 79°42′ to 81°53′ East longitude within the tropics. The mean annual precipitation in Sri Lanka fluctuates from under 900 mm in the driest parts of the southeast and northwest of the country to more than 5000 mm in the wettest parts. Mean annual temperature varies from 27 °C in the coastal areas to 16 °C at Nuwara Eliya in the central highlands, which is 1900 m above mean sea level.

2.2. Data compilation

2.2.1. *Camellia sinensis* occurrence data and resampling

In Sri Lanka, tea (*Camellia sinensis*) habitat range is located between 70–80 °E longitude to 4–5 °N latitude. For model development, occurrence points were taken from Google Earth Pro (Version 7.3.1, Google Inc.), Global Biodiversity Information Facility (GBIF; GBIF; http://www.gbif.org; accessed on March 28, 2018) and relevant literature (Anandacoomaraswamy, 2008; Anandacoomaraswamy et al., 2000, 2002; Balasuriya, 1999; Damayanthi et al., 2010; Jayasekera et al., 2011; Jayasinghe et al., 2018; Tripathi et al., 2004; Wijeratne and Fordham, 1996). The list of tea plantations of Sri Lanka were obtained from the estate registry available at https://www.historyofceylontea.com/tea-estates/estates-registry (accessed on March 20, 2018). This website provides the location of tea estates by its district, town, and regional plantation companies or by its name. This is an official record with very high accuracy and reliability. Occurrence points (using the district or nearest town in Google Earth Pro) were searched, zoomed in on, and manually verified. The coordinates of presence locations were then extracted and recorded. Hence, the noted coordinates are for the actual tea plantations in Sri Lanka. A total of 1310 occurrence points were used from major tea growing districts in Sri Lanka (i.e., Nuwara Eliya, Badulla, Kandy, Ratnapura, Kegalle, Galle, Matara, Matale and Kalutara) covering all 22 agroecological regions (AERs) (Fig. 2). These AERs are classified according to rainfall, elevation and soil type.

The ‘thin()’ function in the spThin package in R software version 2.51 was used (Team, 2017a), with 100 iterations for a given thinning distance of 5 km to increase the performance of the model. Spatial thinning is used to reduce the problems associated with the excessive embodimentof environmental conditions (Anderson, 2003; Kadmon et al., 2004) and spatial sampling biases (Boria et al., 2014; Fourcade et al., 2014; Pearson et al., 2007). The resultant 150 points were converted to CSV format for processing in MaxEnt.

2.2.2. Bioclimatic data

Bioclimatic variables are key elements which govern the distribution of tea species; these variables were extracted from the WorldClim-Global Climate Data (http://www.worldclim.org) (Table 1). WorldClim comprises gridded global climate layers at 30-arc seconds with a spatial resolution of 1 km^2 in CGS_WGS_1984 projection (Rosenzweig, 1995) of records from the 1960–1990 period (Hijmans et al., 2005). Since Sri Lanka has diverse climate condition and topography over a short range, we selected a spatial scale of 1 km for modeling.

2.3. Preprocessing of climate variables

An accurate, biologically informative and generalizable output from the model can be obtained if the model is constructed with predictor variables that have a direct influence on species distribution (Newbold, 2010). Strong collinearity between the variables in SDMs may cause misinterpretation of the model due to the high level of correlation among variables (Ahmadzadeh et al., 2013; Boria et al., 2014; Heikkinen et al., 2006; Peterson and Nakazawa, 2008). Therefore, the correlations among all 19 bioclimatic variables were evaluated using SDM Tools in ArcGIS 10.4.1. Then, the layers that were highly correlated at 0.8 specified level were removed, and the less correlated variables were retained (Pearson correlation coefficient $|r| < 0.8$) for the MaxEnt analysis. The resultant variable set contained seven predictors (Table 1, in bold).

All the environmental variable layers were rasterized into the same boundaries and cell sizes and the same coordinate system as the layer of occurrence localities in ArcGIS 10.4.1 (ESRI, 2015). Then, the environmental variable layers were reprojected to GCS_WGS_1984 with a spatial resolution of 1 km^2. Finally, these layers were converted to ASCII format for further processing in MaxEnt.

2.4. Modeling procedure

The version 3.3.3k of MAXENT (http://www.cs.princeton. edu/˜schapire/MaxEnt/) was used to develop the model. Bioclimatic variables were used to run the MaxEnt program using 10 replicates and the cross-validation run type. Cross-validation is a method that divides the original sample into a training set to train the model, whereas the test set is used to evaluate the model (Phillips, 2008). The MaxEnt model was run with a convergence threshold of 10^{-5}, a maximum number of iterations of 5000, a maximum number of background points as 50,000, and a regularization parameter value of 2, an auto-feature option and the cloglog output format. The new release of Maxent software includes a cloglog transform as the default output format, giving it a stronger theoretical justification than the logistic transform which it replaces by default (Phillips et al., 2017). We used the auto-feature settings, as this optimizes the use of a set of features based on the numbers in the sample size. Phillips and Dudík, 2008a, 2008b selected the following feature classes for continuous variables as default for the corresponding sample sizes: auto-feature classes for at least 80 occurrence records; linear, quadratic and hinge for sample sizes 15–79; linear and quadratic for 10–14 records; and only linear for fewer than 10 records. Regularization denotes model smoothing, alleviating the issues of spatial autocorrelation and model overfitting (Elith et al., 2010, 2011). The regularization multiplier of 2 was used. The default regularization multiplier is 1; a regularization multiplier lower than 1 is likely to result in a more restricted and potentially overfit prediction, whereas a higher regularization multiplier should result in a broader, less discriminating, prediction (Phillips et al., 2006). The “fade-by-clamping” step in the MaxEnt software was used to avoid inaccurate predictions outside the environmental range of training data. Binary habitat suitability maps for the present and future (2050 and 2070) were prepared using the maximum training sensitivity plus the specificity logistic threshold in ArcGIS version 10.4.1 software package. Maximum training sensitivity plus a specificity threshold approach is one of the best methods either for presence/absence data or for presence-only data when random points are used (Liu et al., 2005). A bias file which represents the actual sampling occurrences across the study site can be used as an option in

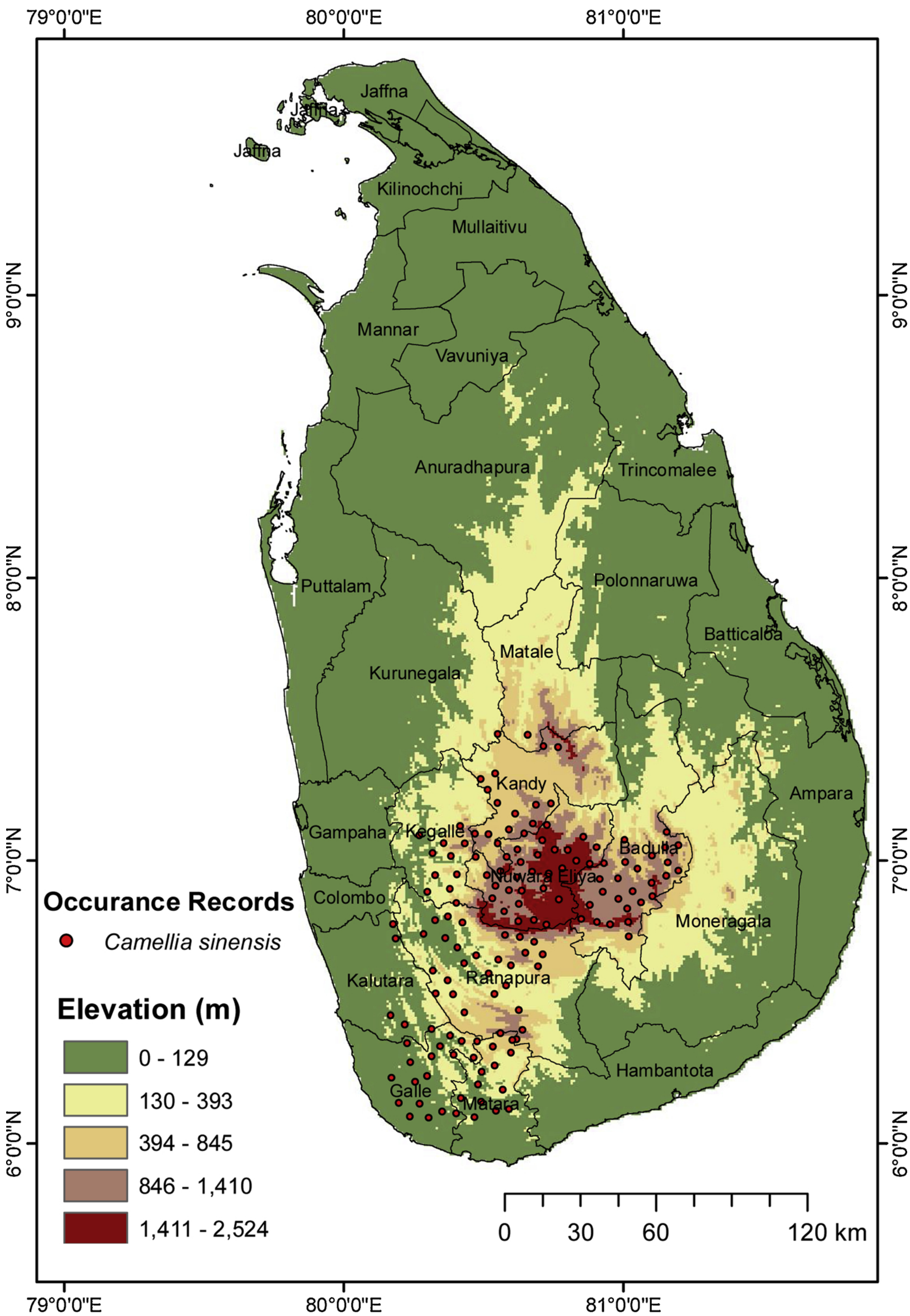

Fig. 2. Study area showing the occurrence records of *Camellia sinensis,* the elevation gradients and districts of Sri Lanka.

the MaxEnt software (Phillips et al., 2009). Thus, the bias file was created using the Gaussian kernel density of sample localities function available in SDM tools.

2.5. Evaluation of model performances

To evaluate the accuracy and the quality of predictions, the database was divided into two subsets: calibration and evaluation. As the first step, a random sample from 75% of the total database was used to calibrate (train) the model, whereas the next step, comprising the remaining data (25%), was used to evaluate (test) the model predictions. First, the AUC and Cohen's kappa were used, as they are widely used in prediction accuracy assessment (Allouche et al., 2006; Byrt et al., 1993; Feinstein and Cicchetti, 1990; Landis and Koch (1977); Lantz and Nebenzahl, 1996; Shao and Halpin, 1995).

The receiver operating characteristic (ROC) curve and the area under the curve (AUC) (Elith et al., 2006; Phillips et al., 2006) were used to test model performance. AUC provides a threshold-independent assessment of model performance using a web-based program (Vanagas, 2004), which varies from 0.5 to 1. An AUC value of 0.5 represents a model with random predictions, and values close to one represent higher discrimination. An AUC value between 0.9 and 1.0 shows excellent model performance; 0.8–0.9 = good; 0.7–0.8 = average; 0.6–0.7 = poor, and 0.5–0.6 = insufficient (Thuiller et al., 2006). The AUC values should be carefully interpreted, as they provide the same weights to commission and omission errors (Lobo et al., 2008;

Table 1
Bioclimatic variables used for modeling the climate suitability habitat of *Camellia sinensis* in Sri Lanka. Note: The selected climatic and environmental variables for model development are shown in **bold**.

Source	Data Type	Variables	Abbreviations	Units
WorldClim – Global Climate Data	Bioclimatic	**Annual mean temperature**	**BIO1**	**°C**
		Mean diurnal range	**BIO2**	**°C**
		Isothermality	BIO3	Unitless
		Temperature seasonality	**BIO4**	**Unitless**
		Max temperature for warmest month	BIO5	°C
		Min temperature for coldest month	BIO6	°C
		Temperature annual range	BIO7	°C
		Mean temperature of wettest quarter	BIO8	°C
		Mean temperature of driest quarter	BIO9	°C
		Mean temperature of warmest quarter	BIO10	°C
		Mean temperature of coldest quarter	BIO11	°C
		Annual precipitation	**BIO12**	**Mm**
		Precipitation of wettest month	BIO13	Mm
		Precipitation of driest month	**BIO14**	**Mm**
		Precipitation seasonality	**BIO15**	**Unitless**
		Precipitation of wettest quarter	**BIO16**	**Mm**
		Precipitation of driest quarter	BIO17	Mm
		Precipitation of warmest quarter	BIO18	Mm
		Precipitation of coldest quarter	BIO19	Mm

Peterson and Nakazawa, 2008).

Cohen's kappa (k) (Shao and Halpin, 1995) measures the overall accuracy of the model predictions by the accuracy expected to occur by chance (confusion matrix) (Table 2). The kappa value ranges from −1 to 1. The maximum kappa (k) value is close to 1, which means the prediction effect is very high. Landis and Koch (1977) have suggested the following ranges of agreement for the kappa statistic: poor accuracy, $k < 0.4$; good accuracy, $0.4 < k < 0.75$; and excellent accuracy, $k > 0.75$. Several studies have shown pitfalls in using a kappa that is inherently dependent on prevalence (Byrt et al., 1993; Cicchetti and Feinstein, 1990; Lantz and Nebenzahl, 1996). Therefore, other than AUC and kappa, we calculated a threshold-dependent statistical matrix called true skill statistics (TSS) (Table 3) (Allouche et al., 2006). We used the threshold value as 0.5, as it is widely used in ecology and species distribution models (Pearson et al., 2002). The TSS is considered an additional accuracy measurement that is not affected by prevalence and the size of the validation set, where kappa usually gives very low values with presence data only. The TSS accounts for both omission and commission errors and ranges from −1 to +1, where +1 indicates perfect agreement, and 0 represents a random fit (Allouche et al., 2006). The evaluation statistics were calculated using the ROCR, vcd and boot packages implemented in R software version 3.5.1 (Team, 2017b).

The jackknifing procedure was used to assess the contribution of the different bioclimatic variables to the model based on the "leave-one-out" basis suggested by Peterson et al. (2011). Predictors that produced the highest training gains are taken to be the most significant bioclimatic variables (Kouam et al., 2010). The response curves that illustrate the relationships between the probability of species present and the environmental variables were also examined. In the Jackknife procedure, each variable is omitted and the model is readjusted and rebuilt with the remaining variables (Phillips et al., 2006).

The two methods were used to evaluate the relative contribution of environmental variables to the model (i.e., the percentage contribution,

Table 2
Confusion matrix used to evaluate the predictive accuracy of model.

Predicted	Actual	
	Presence	Absence
Presence	True Positive (a)	False Positive (b)
Absence	False Negative (c)	True Negative (d)

Table 3
Measures and formulas of predictive accuracy indicators for the developed model.

Measure	Formula
Overall accuracy (P_o)	(a + d)/n
Random accuracy (P_r)	$(a + b)\times(d + c)+(c + a)\times(b + a)/ (\text{Total})^2$
True positive rate (sensitivity)	a/(a + c)
True negative rate (specificity)	d/(b + d)
True skills statistics	sensitivity + specificity – 1
Kappa statistic	(Overall accuracy (P_o) – Random accuracy (P_r))/1-Random accuracy(P_r)

permutation importance and the jackknife test). These contribution percentages are questionable, as they depend highly on the specific way that the different algorithms could get to the same solution through a different path with a different percentage of contributions (Kalle et al., 2013). The permutation importance measure depends only on the final MaxEnt model, and the contribution of each variable, which is determined by randomly interchanging the values of that variable among the training points (Phillips, 2008). In a jackknife test, a model is created using each variable in isolation and shows which variables have the most useful information independent of the others, whereas the heuristic test does not make that distinction (Kalle et al., 2013).

2.6. Future projection

The same seven variables were then selected and employed to model potential future climate suitability for 2050 and 2070. The potential distribution of the *Camellia sinensis* under future climate was modeled using two global climate models, *viz.*, CCSM4 (Community Climate System Model, version 4) and MIROCH-H (Model for Interdisciplinary Research on Climate). Mishra et al. (2014) and Sharmila et al. (2015) reported that the MIROC5 can be used to predict the spatial and temporal distribution of climate attributes of the South Asian region more reliably. Watanabe et al. (2010) reported that the MIROC5 has a better simulation of the mean climate, variability, and climate change because of anthropogenic and natural radiative forcing. The CCSM4 has also been reported to better model temperature and precipitation variables for the Asian region, especially India (Chaturvedi et al., 2012).

For the projections of the potential future distribution of tea species,

Table 4
Projected change in monthly average temperature (Avg. Temp.) and precipitation (Avg. Prec.) compared to historical mean.

Global Climate Models (GCMs)	Representative Concentration Pathway (RCPs)	2020-2039		2040-2059		2060-2079	
		Avg. Temp. (°C)	Avg. Prec. (mm)	Avg. Temp. (°C)	Avg. Prec. (mm)	Avg. Temp. (°C)	Avg. Prec. (mm)
MIROC5	RCP 2.6	28	100.7	28.3	110.2	28.3	108.3
	RCP 6.0	27.9	108.9	28.2	105.5	28.5	110.2
	RCP 8.5	28.1	96.8	28.6	101.2	29.3	120.0
CCSM4	RCP 2.6	27.6	192.8	27.7	201.8	27.7	207.2
	RCP 6.0	27.6	206.8	27.9	206.1	28.2	202.1
	RCP 8.5	27.7	214.8	28.3	206.2	29.0	213.0
Historical (1901 – 2015)		26.6 °C			142.0 mm		

corresponding data layers of both general circulation models (GCMs) were downloaded from WorldClim (http://www.ccafs-climate.org/) for three emission scenarios [Representative Concentration Pathway (RCP) 2.6, 6.0 and 8.5] at a 30-second spatial resolution. The numbers in each RCP refer to the amount of radiative forcing produced by greenhouse gases in 2100. As per the IPCC (2013), RCP 2.6 is a very low range value for radiative forcing, RCP 6.0 is the medium future emission scenario with total radiative forcing that could reach almost + 6.0 W/m^2 (650 ppm CO_2) by the end of the 21st Century, remaining steady thereafter, whereas the RCP 8.5 is an extreme carbon emission scenario that continues to increase throughout the 21st century, with radioactive forcing attaining almost + 8.5 W/m^2 (935 ppm CO_2).

Monthly average temperature and precipitation in Sri Lanka were calculated using the climate change knowledge portal (Climate Change Knowledge Portal, 2015) for three time windows— 2020–2039, 2040–2059 and 2060–2079—for different RCPs using MIROC5 and CCSM4, as shown in Table 4. Table 4 indicates that the monthly temperature and precipitation will increase in the future. Monthly average precipitation may be low during the period from 2020 to 2039 under RCP 8.5 when using MIROC5 in comparison with other RCP levels in the same condition, whereas the highest temperature will result under RCP 8.5 under CCSM4 model.

After modeling the species distribution, the likely changes in the suitability areas were calculated for the future compared to the current time period using maps and spatial analysis tools available in the ArcGIS 10.4.1 software. The suitability maps, current and future, produced by the model, ranged from 0 to 1. We used maximum training sensitivity plus specificity thresholds to convert the distribution data to binary maps showing suitable and unsuitable habitat for tea and reclassified the tea to four classes of climate suitability using the natural breaks (Jenks) option available in ArcGIS layer properties, *viz.*, "optimal" (> 0.6), "medium" (0.4 – 0.6), "marginal" (0.2 – 0.4), and "unsuitable" (< 0.2). Area calculation for the suitability classes was carried out in the ArcGIS environment.

3. Results

3.1. Presence data

Presence data includes samples of locations where species are known to inhabit. Tea plants are grown in the elevation all the way up to 2500 m, and tea growing regions occupy three different elevation zones: low-grown (sea level to 600 m), mid-grown (600–1200 m) and high-grown (1200 m upward) based on geography and climate (Fig. 2). Additionally, low-grown tea is mainly grown in the southern part of the country, as shown by occurrence records in Fig. 2.

3.2. Species distribution model

The default output of MaxEnt is cloglog, which gives a result between 0 to 1 of the probability of habitat suitability. Potential habitat with optimal suitability thresholds was distributed in the existing tea growing districts of Galle, Matara, Sabaragamuwa, Nuwara Eliya, Kandy, Badulla and Matara. The average test AUC for the replicate runs was 0.92, and the standard deviation was 0.016. ROC curves for species distribution map indicated a high accuracy (AUCtraining = 0.92 (S.D. = 0.004), and AUCtest = 0.93 (S.D. = 0.004). High AUC values show that the model predictions are reliable. The future suitability distribution of tea predicted by the model produced a high success rate with high AUCs for all tested RCPs under both GCMs (Table 5). This shows that the climatic variables used for this model led to excellent prediction results. The TSS values with a mean 0.847 ± 0.007 signify the accuracy of predicting suitability habitats of tea by the use of presence-only data. The maximum kappa values (k) of the current and future models are approximately 0.454 ($0.4 < k < 0.75$), and they indicate that the overall performance of the model was good (Landis and Koch, 1977) (Table 5).

Table 6 gives permutation importance of the predictor variables to the MaxEnt model. Among the input environmental variables, precipitation seasonality (coefficient of variation) (BIO15) was the most influential and contributed 67.6% to the distribution model. Annual mean temperature (BIO1) and annual precipitation (BIO12) contributed 15.7% and 7.6%, respectively. The mean diurnal range (BIO2) also had a substantial influence on the habitat model, which was 3.5%, and temperature seasonality (BIO4) and precipitation of the wettest quarter (BIO16) contributed 2.6% and 2.5%, respectively. Precipitation of the driest month (BIO14) contributed only 1.1%, which was the lowest contribution as shown in Table 6. At the same time, models based on the contributions of the environmental variables showed that mean

Table 5
Results of AUC, TSS and kappa tests for *camellia sinensis*.

Year	Global Climate Models (GCMs)	Representative Concentration Pathway (RCPs)	Threshold Independent (AUC)			Threshold Dependent	
			Training	Test	Standard Deviation	TSS	Max. kappa (k)
2050	MIROC5	RCP 2.6	0.956	0.950	0.005	0.868	0.461
		RCP 6.0	0.956	0.955	0.007	0.767	0.430
		RCP 8.5	0.952	0.949	0.006	0.886	0.466
	CCSM4	RCP 2.6	0.932	0.920	0.008	0.835	0.451
		RCP 6.0	0.935	0.920	0.009	0.847	0.455
		RCP 8.5	0.934	0.919	0.009	0.790	0.438
2070	MIROC5	RCP 2.6	0.957	0.945	0.006	0.883	0.465
		RCP 6.0	0.955	0.950	0.010	0.881	0.465
		RCP 8.5	0.953	0.946	0.006	0.888	0.466
	CCSM4	RCP 2.6	0.958	0.948	0.006	0.882	0.465
		RCP 6.0	0.932	0.915	0.008	0.834	0.451
		RCP 8.5	0.930	0.929	0.008	0.836	0.452
Current			0.932	0.933	0.004	0.815	0.445

Table 6
Percentage contribution and permutation importance of the predictor variables to the MaxEnt model.

Environmental variable	Percent contribution	Permutation Importance
Precipitation Seasonality (BIO15)	15.7	67.6
Annual Mean Temperature (BIO1)	40.2	15.7
Annual Precipitation (BIO12)	17	7.0
Mean Diurnal Range (BIO2)	6.3	3.5
Temperature Seasonality (BIO4)	6.1	2.6
Precipitation of Wettest Quarter (BIO16)	1.5	2.5
Precipitation of Driest Month (BIO14)	13.2	1.1

temperature (BIO1) showed the greatest impact (40.2%) followed by precipitation seasonality (Bio15) (15.7%) (Table 6).

The Maxent model's jackknife analysis of variable importance resulted in precipitation seasonality (coefficient of variation) (BIO15), annual mean temperature (BIO1) and annual precipitation (BIO12) being the three most important predictors of *C. sinensis* habitat distribution (Fig. 3), indicating these contain the most useful and distinctive information in defining these species distributions. The jackknife test of variable importance in *C. sinensis* showed considerable change when the precipitation of the driest month (BIO14) and mean diurnal range (BIO2) were used in isolation. Temperature seasonality (BIO4) had a moderate gain when used separately (Fig. 3).

The quantitative relationship between the logistic probability of the presence and bioclimatic variables can be determined through response curves, as shown in Fig. 4. One of the key bioclimatic variables describing the current and future spatial distributions of *Camellia sinensis* was precipitation seasonality. Precipitation seasonality is an index of the ratio of the standard deviation of the monthly total precipitation to the mean monthly total precipitation which is expressed as a percentage, with a higher index value indicating greater variability. Greater seasonality reflects greater variability in monthly precipitation, which is illustrated by precipitation seasonality (BIO15), as the degree of precipitation variation over a given period. The response curve for BIO15 showed that the highest probability of *Camellia sinensis* presence was connected with areas where the precipitation seasonality value is approximately 30 and habitat suitability decreases with the increment of variation (Fig. 4A).

According to the response curves, high probabilities of presence were predicted when the annual mean temperature (BIO1) ranged from 13 to 28 °C, whereas its distribution was strongly constrained at 20 °C (Fig. 4B). The response curve of annual precipitation (BIO12) showed that *Camellia sinensis* preferred to have high precipitation ranges from 2000 to 5000 mm (Fig. 4C). The response curve of the mean diurnal temperature range (BIO2) (Fig. 4D) showed that habitat suitability of tea is associated with areas where the mean diurnal temperature values ranged from 5 to 9.5 °C. Greater seasonality reflects greater variability in temperature, which is illustrated by temperature seasonality (BIO4) (Fig. 4E) as the degree of temperature variation over a given period. The response curve for BIO4 showed that the habitat suitability of tea drastically decreases with high-temperature variation that is above 40 °C. Based on the response curves of precipitation of driest month (BIO16) (Fig. 4F) and temperature seasonality (BIO14) (Fig. 4G), the habitat suitability of the tea increases with the increasing precipitation of the wettest quarter from 800 to 1800 mm, whereas this habitat fares better when it has more than 30 mm of precipitation in driest months. However, BIO16 and BIO14 did not influence the habitat suitability significantly (Table 6).

3.3. Current and future projections

Climate suitability classes can be categorized as unsuitable, marginal, medium and optimal, as shown in Figs. 5 and 6 and Table 7. The model shows that the suitable habitats of *Camellia sinensis* will change under global climate models (GCMs) of MIROC5 and CCSM4 under the three tested RCP's (2.6, 6 and 8.5) by 2050 and 2070, respectively, compared to the current climate distribution (Figs. 5, 6 and Table 7).

According to the current climate suitability, an area of 48,595 km^2 in Sri Lanka is has unsuitable climate conditions for tea, which represents 74.1% of total area. It has 5086 km^2 (7.8%) of marginal suitability and 5769 km^2 (8.8%) of medium suitability. Areas with optimal current habitat suitability where the equal training sensitivity was equal to the plus specificity threshold accounted for only 6090 km^2 (9.3%) of the country (Table 7). Areas under medium and optimal classes belong to existing tea grown districts of Nuwara Eliya, Badulla, Kandy, Ratnapura, Galle, Matara, Matale, and Kegalle which represent different elevations (Fig. 5 and 6).

Camellia sinensis may have significant dynamism in terms of suitability with respect to future climate scenarios. Compared to the current climate suitability map, in the year 2050, under both GCMs of MIROC5 and CCSM4, most of the medium and optimal suitability areas in the low elevation (e.g., Galle and Matara) will be lost at a greater rate in comparison to the mid- and high elevation areas for all tested RCPs (Fig. 5). However, areas of marginal suitability will increase in Galle and Matara, whereas the suitability range continues to narrow in the vicinity of the upper extent along Kalutara, Colombo, Kandy and Matale (Fig. 5).

In the year 2050, most current optimal suitable areas for tea in the central hills (i.e., Nuwara Eliya and some parts of Kandy district) will increase under the three tested RCPs with MIROC5 and CCSM4 (Fig. 5). On par with current suitability map, most areas with have optimal suitability will remain unchanged in the lower parts of Nuwara Eliya, whereas the upper parts in Nuwara Eliya will alter its' climate suitability in both GCMs.

Fig. 5 also shows that optimally suitable areas will increase

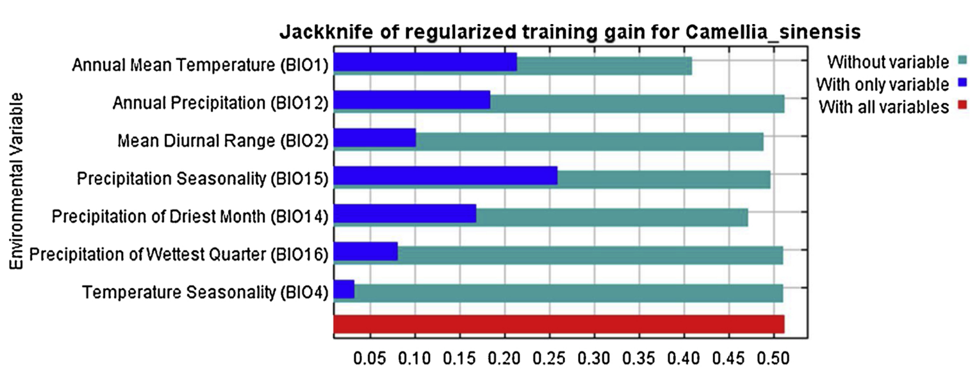

Fig. 3. Results of jacknife evaluations of the relative importance of predictor variables and their percentage contribution in Maxent model for *Camellia sinensis* species in Sri Lanka.

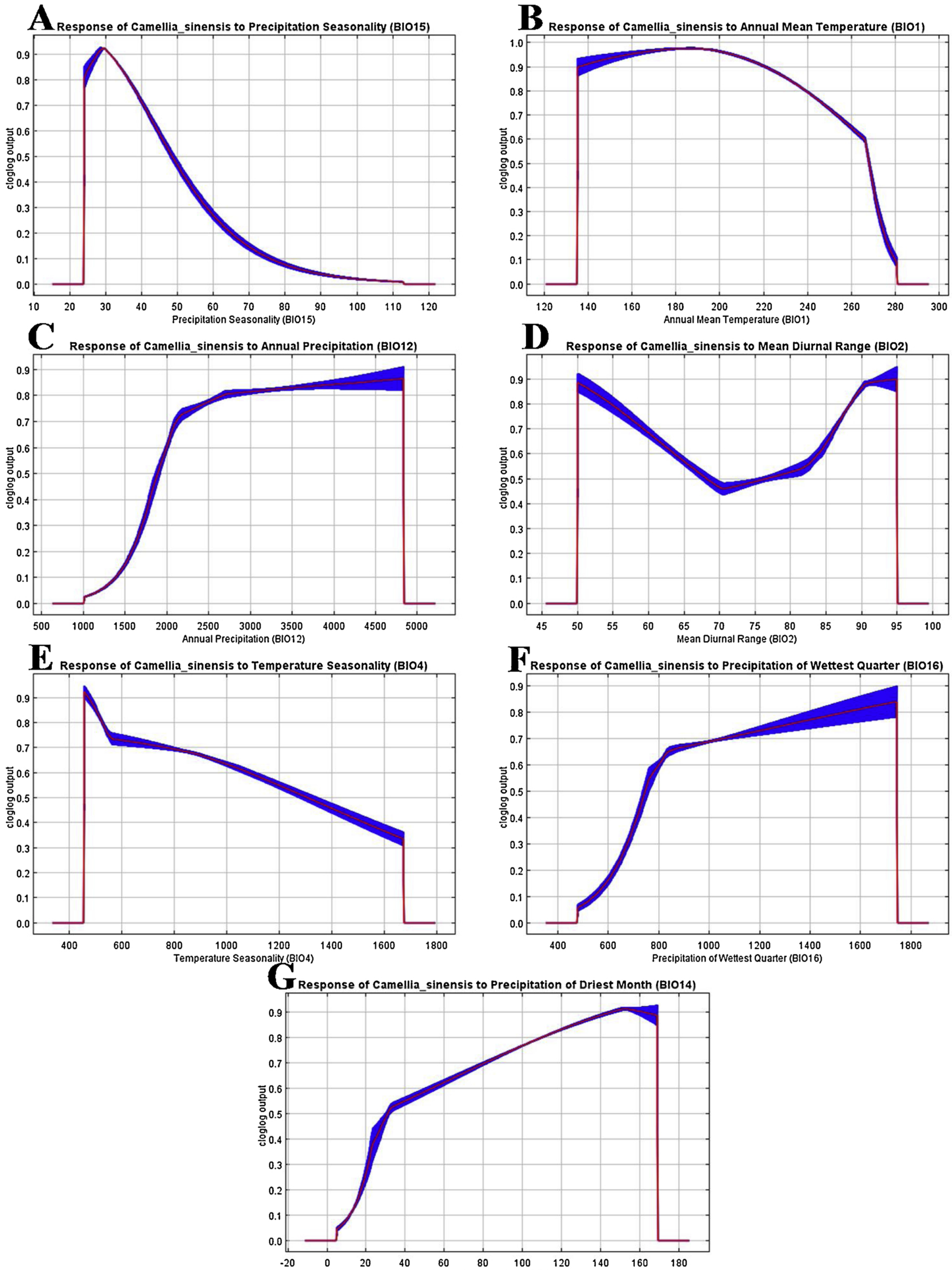

Fig. 4. Response curves for the major predictors of climate suitability habitats of *Camellia sinensis* according to the MaxEnt model.

substantially in the Ratnapura district, whereas some areas in Badulla become less optimal in 2050 under both GCMs. In 2050, the average marginal and medium suitability areas (6.6% and 7.2%, respectively) will become less difficult under MIROC5 than that of areas under CCM4. A substantial difference existed in the projections of the RCP 2.6 under MIROC5 in 2050 for optimal suitability (9.9% of suitability area) (Fig. 5 and Table 7) when compared to the results for RCP 2.6 under CCM4 (8.2%) and current climate (9.3%). An apparent increment (e.g., 6.4% increment in optimal suitability under RCP 2.6 under MIROC5 in the year 2050) will extend the optimal range further north toward Kandy and spread over the Ratnapura district. In the Ratnapura district, areas of climatic suitability for tea are projected to have dynamic changes, with shifts from medium suitability to optimal climate suitability in 2050. However, in comparison to the current climate, by 2050

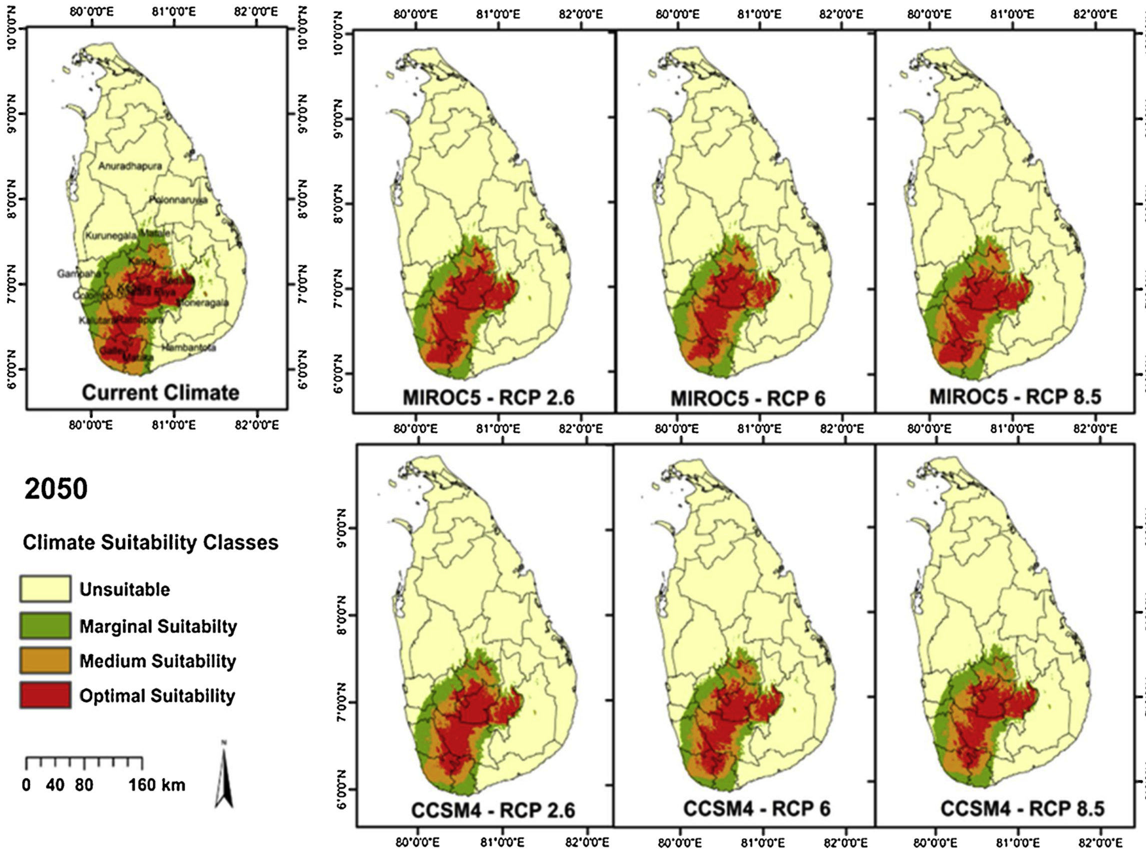

Fig. 5. Projected distribution maps of *Camellia sinensis* showing likely unsuitable, marginal, medium and optimal areas under RCP 2.6, RCP 6 and RCP 8.5 in 2050 with respect to the current time period.

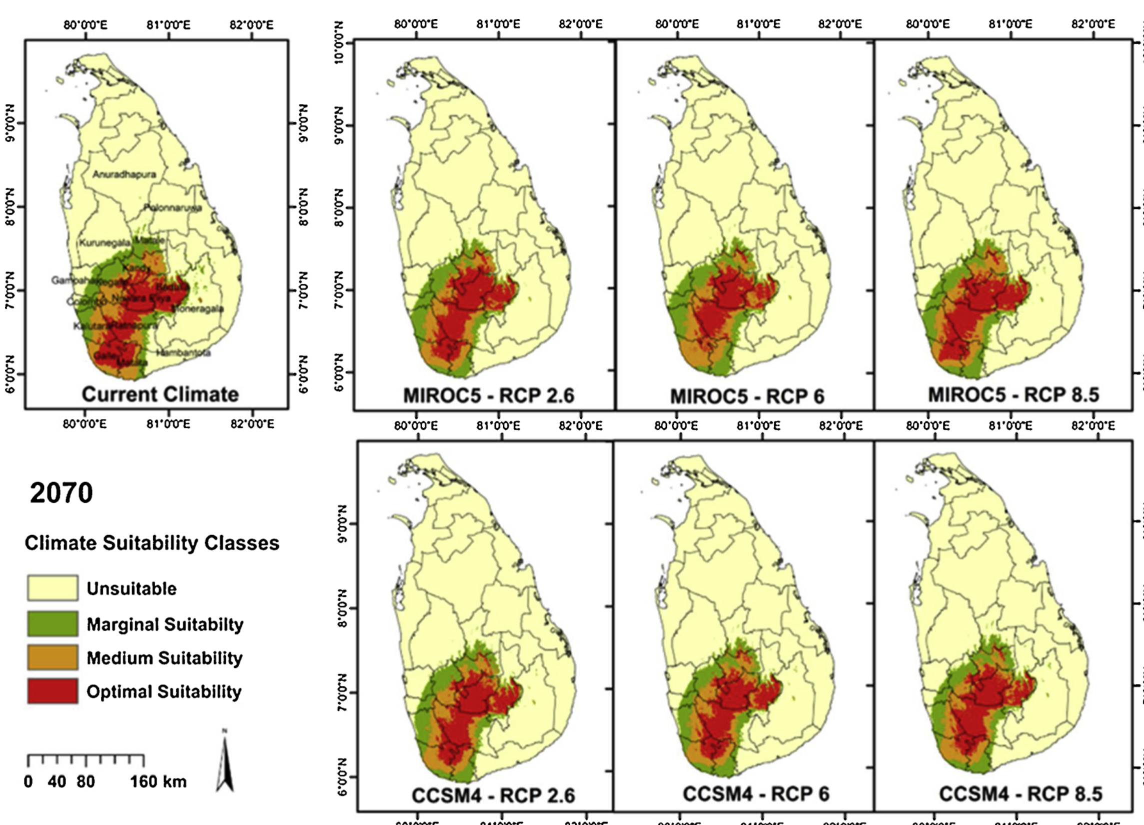

Fig. 6. Projected distribution maps of *Camellia sinensis* showing likely unsuitable, marginal, medium and optimal areas under RCP 2.6, RCP 6 and RCP 8.5 in 2070 with respect to the current time period.

Table 7
Areas under different suitability classes (km^2) of *Camellia sinensis* by 2050 and 2070 under RCP 2.6. 6.0 and 8.5 under GCMs of MIROC5 and CCSM4.

Year	Global Climate Models (GCMs)	Representative Concentration Pathway (RCPs)	Area under different suitability classes in km^2 (Percentage is shown in brackets)			
			Unsuitable	Marginal	Medium	Optimal
2050	MIROC5	RCP 2.6	50593 (77.2%)	4197 (6.4%)	4258 (6.5%)	6492 (9.9%)
		RCP 6.0	50508 (77.1%)	4532 (6.9%)	5039 (7.7%)	5460 (8.3%)
		RCP 8.5	50481 (77.0%)	4345 (6.6%)	4894 (7.5%)	5820 (8.9%)
		Average Area	50527 (77.1%)	4358 (6.6%)	4730 (7.2%)	5924 (9.0%)
	CCSM4	RCP 2.6	50534 (77.1%)	4895 (7.5%)	4716 (7.2%)	5394 (8.2%)
		RCP 6	51063 (77.9%)	4472 (6.8%)	5012 (7.6%)	4992 (7.6%)
		RCP 8.5	50567 (77.2%)	5119 (7.8%)	4894 (7.5%)	4960 (7.6%)
		Average Area	50721 (77.4%)	4829 (7.4%)	4874 (7.4%)	5115 (7.8%)
2070	MIROC5	RCP 2.6	50480 (77.0%)	4504 (6.9%)	4650 (7.1%)	5905 (9.0%)
		RCP 6.0	50335 (76.8%)	5115 (7.8%)	5442 (8.3%)	4647 (7.1%)
		RCP 8.5	50639 (77.0%)	4672 (7.1%)	4708 (7.2%)	5720 (8.7%)
		Average Area	50485 (77.0%)	4764 (7.3%)	4934 (7.5%)	5424 (8.3%)
	CCSM4	RCP 2.6	50535 (77.1%)	4902 (7.5%)	4718 (7.2%)	5384 (8.2%)
		RCP 6.0	50770 (77.5%)	4821 (7.4%)	4713 (7.2%)	5237 (8.0%)
		RCP 8.5	50686 (77.3%)	4860 (7.4%)	4518 (6.9%)	5475 (8.4%)
		Average Area	50663 (77.3%)	5086 (7.4%)	5769 (7.1%)	5365 (8.2%)
Current Climate		Average Area	48595 (74.1%)	5086 (7.8%)	5769 (8.8%)	6090 (9.3%)

and 2070, most of the areas in the Ratnapura district may have received better climatic conditions for tea cultivation.

According to Table 7, a similar percentage is found for the CCSM4 for the areas under marginal and medium suitability in the year 2050. The CCSM4 model indicates the same percentage of 7.6% in areas with climatic optimal suitability under RCP 6 and 8.5 in the year 2050. By 2050, the average unsuitable areas under MIROC5 and CCSM4 will represent 77.1% and 77.4% of the area, respectively (Table 7).

Generally, by 2070, optimal suitability areas and medium suitability areas may decrease under all RCPs using MIROC5 compared to the current climate suitability across the low, mid- and high elevations, with higher losses being exhibited in the low elevations (i.e., Galle and Matara). Tea cultivation in the optimal climate suitability areas of high and low elevation will be influenced by different RCPs under both GCMs, but the impact may be higher under RCP 6 of MIROC5 compared to CCSM4.

The climate change scenario in the year 2070 indicates that in low elevation areas such as Galle and Matara, a shift in climatic suitability can be observed, with areas previously designated as having optimal suitability changing to areas of medium or marginal suitability in all RCPs under both tested models. Areas having optimal climate suitability in Galle and Matara will be considerably reduced under the influence of RCP 6 under MIROC5 by 2070. The decrease in optimal suitability areas will be higher in the Matara district than Galle under all RCPs of both GCMs for the years 2050 and 2070. A reduction of areas under medium suitability classes can be clearly seen in the lower belt of Matara and Galle in the southern part with respect to all RCPS under both GCMs (Fig. 5 and 6).

Moreover, in 2070, both GCMs project a loss of optimal climate suitability areas in Badulla district and an increase of optimal suitability in Ratnapura, the upper part of Kandy and Nuwara Eliya districts. Additionally, under the RCP 2.6 and according to the MIROC5, by 2050 and 2070, more expansion of optimal suitability areas can be expected in the hilly areas of the central part, whereas less expansion will be seen under the same conditions using CCSM4.

Camellia sinensis may contract its marginal suitability in all RCPs under both GCMs by the year 2050 and 2070 compared to the current suitability habitats. The CCSM4 and MIROC5 models indicate a reduction of areas in the Matale and Kegalle districts with marginal climatic suitability by 2070. In contrast, a major expansion of areas of marginal suitability will occur in some parts of the Kandy district under all RCPs of CCSM4 by 2070, and in the whole southern belt, including Matara and Galle, under both GCMs by 2050 and 2070. Interestingly, RCP 6.0 under MIROC5 in 2070 will exhibit a similar percentage of total areas of marginal suitability (7.8%) when compared to the results for the current climate.

The projected percentage of medium suitability areas in 2070 under RCP 2.6 and 8.5 for MIROC5 and RCP 2.6 and 6.0 of CCSM4 is approximately similar at 7.2% (Table 7). However, MIROC5 projects an increase in the marginal suitability category, whereas under CCSM4, the average area of marginal suitability remains unchanged and the areas of medium suitability decrease from the year 2050 to 2070. Furthermore, RCP 6.0 under MIROC5 forecasts the same percentage of medium suitability habitats for tea by the year 2050 and 2070. Optimal suitability areas are projected to increase under MIROC5 using RCP 2.6 by 2050, with a 6% increment, compared to current conditions, but it will decrease by 9.1% in 2070 under the same scenario.

The lands of medium suitability occupied in 2050 are likely to disappear, especially under RCP 6.0 and 8.5 under CCSM4 by 2070, as a result of being converted areas that are unsuitable or marginally suitable (Figs. 5 and 6). As per the predicted results, in all RCPs in 2050 and 2070 under both GCMs, the distribution of areas of optimal and marginal suitability in the Moneragala district will be reduced as some of the patches (indicated in red) disappear in some of the areas in mid- and high elevations, as shown in Figs. 5 and 6.

Moreover, RCPs 6.0 and 8.5 also show a similar percentage of optimal climate suitability under MIROC5 in 2050, as well as the same percentage of marginal suitability under CCSM4 in 2070. The model prediction for almost all scenarios (RCP 2.6, 6.0, and 8.5) in the year of 2050, as well as 2070, reveals that areas 'unsuitable' for tea would increase relative to the current potential distribution area (Table 7). Even though unsuitable areas will increase from current to future, all RCPs under CCSM4 show approximately the same percentage of the area having climate unsuitability (77.3%) in both years of the 2050 and 2070. Under MIROC5, few changes will occur in the unsuitable areas from the year 2050–2070. Under the scenario of RCP 2.6, 6.0, and 8.5, for all the selected time periods (2050 and 2070) and selected GCMs, the areas with optimal, medium and marginal climate suitability are expected to show substantial changes, resulting in a large area of the current distribution to become low potential by 2050 and 2070.

3.4. Percentage loss (-) or gain (+) of suitability areas

Overall, *Camellia sinensis* will experience loss in areas of optimal suitability at higher percentages under the GCM scenarios of CCSM4, representing an average percentage of 16% and 11.9% by 2050 and 2070, respectively, compared to the current optimal suitability (Table 8). The results signify that future climate in both 2050 and 2070

Table 8
Percentage of loss (-) or gain (+) of area of suitability (%) for *Camellia sinensis* by 2050 and 2070 under RCP 2.6, 6.0, and 8.5 using GCMs of MIROC5 and CCSM4.

Year	Global Climate Models (GCM)	Representative Concentration Pathway (RCPs)	Percentage of loss (-) or gain (+) of suitability area (%)			
			Unsuitable	Marginal	Medium	Optimal
2050	MIROC5	RCP 2.6	4.1	−17.5	−26.2	6.6
		RCP 6.0	3.9	−10.9	−12.7	−10.3
		RCP 8.5	3.9	−14.6	−15.2	−4.4
		Average %	**4.0**	**−14.3**	**−18.0**	**−2.7**
	CCSM4	RCP 2.6	4.0	−3.7	−18.3	−11.4
		RCP 6.0	5.1	−12.1	−13.1	−18.0
		RCP 8.5	4.1	0.6	−15.2	−18.6
		Average %	**4.4**	**−5.1**	**−15.5**	**−16.0**
2070	MIROC5	RCP 2.6	3.9	−11.4	−19.4	−3.0
		RCP 6.0	3.6	0.6	−5.7	−23.7
		RCP 8.5	3.9	−8.4	−18.6	−6.4
		Average %	**3.8**	**−6.4**	**−14.6**	**−11.0**
	CCSM4	RCP 2.6	4.0	−3.6	−18.2	−11.6
		RCP 6.0	4.5	−5.2	−18.3	−14.0
		RCP 8.5	4.3	−4.4	−21.7	−10.1
		Average %	**4.3**	**−4.4**	**−19.4**	**−11.9**

can affect the optimal suitability of the tea growing areas, particularly under RCP 8.5 in 2050 and RCP 6.0 in 2070 under CCSM4. Under GCM of CCSM4, the loss of percentage of optimal climate suitability will be 2.7% and 11% by the years 2050 and 2070, respectively. Moreover, the loss is greater under RCP 6.0 than the other RCP levels (Table 8).

Proportionately, a high percentage of medium suitability land will be lost under RCP 2.6 of MIROC5, marking an overall loss of 18.0% for the year 2050. The reduction of space for tea in an area with climate of medium suitability will be higher in CCSM4 (19.4%) than in MIROC5 by 2070 and will show the highest decline from RCP 8.5.

Under RCP2.6 of MIROC5, MaxEnt predicted the highest loss in habitat area of marginal suitable with 17.5% in 2050 while CCSM4 recorded average loss in the marginal suitable climate space as 4.4%. The gain in unsuitable land will range from 3.8 to 4.4%, resulting in a high percentage of area (5.1%) in the unsuitable class by 2050 under RCP 6 of CCSM4 (Table 8).

3.5. Contributions of bioclimatic variables for suitability habitats of tea by 2050 and 2070

In future climate conditions in 2050 under the two GCMs, precipitation seasonality will be the most influential climatic predictor for *Camellia sinensis,* similar to the current climate model. According to the RCPs under MIROC5 model, the second and third important climatic variables will be annual precipitation and annual mean temperature, respectively (Table 9). The same variables will appear to be the key climate predictors for tea distribution by 2070 (Table 9).

4. Discussion

This study investigated current potential and future projections of climate suitability of *Camellia sinensis* in Sri Lanka using the MaxEnt species distribution model. The MaxEnt model projected habitat suitability map of *Camellia sinensis* based on existing data sets with mean AUC of 0.91. According to the pragmatism suggested by Hosmer and Lemeshow (2000), the predictive capacity of a model may be considered outstanding in the case of AUC values greater than 0.9. Also, TSS and kappa values indicating the overall performance of the model was good. Therefore, we consider our model performances are robust and adequate for construing the overall climate suitability habitat distribution of tea species in Sri Lanka.

Climate plays a significant role in defining a species' distribution

Table 9
Contribution of bioclimatic variables of RCPs for suitability of tea by 2050 and 2070 under GCMs of MIROC5 and CCSM4.

Variable	Contribution % of RCPs under MIROC5 and CCSM4 by 2050						Contribution % of RCPs under MIROC5 and CCSM4 by 2070					
	RCP 2.6		RCP 6.0		RCP 8.5		RCP 2.6		RCP 6.0		RCP 8.5	
	MIROC5	CCSM4	MIROC5	CCSM4	MIROC5	CCSM4	MIROC5	CCSM4	MIROC5	CCSM4	MIROC5	CCSM4
Precipitation Seasonality (BIO15)	17.3	37.9	6.5	45	22.9	62.6	14.8	61.3	7.7	59.9	37.8	44.9
Annual Mean Temperature (BIO1)	22.4	26.7	28.9	19.9	21.7	15.1	25	19.7	22.5	17.8	18.3	26.2
Annual Precipitation (BIO12)	22.5	10.2	16.9	16.9	16.5	7.7	16.4	6.8	2.5	8.7	10.5	8
Mean Diurnal Range (BIO2)	18.5	11.2	16.5	10.1	17.6	8.9	17.2	6.1	8.3	6.8	15.5	6.9
Temperature Seasonality (BIO4)	10.9	12.7	28.1	3.9	14.1	3.2	15.7	3.8	50.8	8.7	15.6	12.1
Precipitation of Wettest Quarter (BIO16)	8.3	1.2	2.8	3.8	7.0	2.5	10.6	1.2	8	1	2.2	1.4
Precipitation of Driest Month (BIO14)	0.1	0.1	0.3	0.3	0.2	0.1	0.4	1.1	0.1	0.3	0.1	0.4

and assessing the interactions between abiotic and biotic factors (Morelle et al., 2015). Our model predicted the current and future habitats at different climate suitability conditions where *Camellia sinensis* can potentially establish in Sri Lanka (Figs. 5 and 6). Furthermore, potential distribution ranges of *Camellia sinensis* for current climate concurred with the well-known distribution of the tea cultivations in Sri Lanka (Fig. 1), which are mainly concentrated in the central highlands and southern areas of the landmass. Sri Lanka tea cultivation is broadly categorized according to elevation and we focused discussion by districts of Nuwara Eliya, Matara, Ratnapura, Galle, Matale, Kegalle, Kalutara, Moneragala and Badulla for ease of interpretation of MaxEnt output.

The forecasted changes in forthcoming climates have the potential to thrust tea cultivation into situations and extremes which have not been experienced previously. The suitability of tea production in Sri Lanka under future climate conditions changes drastically over all the major tea growing regions. Some of the consequences of climate change could have advantageous effects, whereas others are expected to be disadvantageous. We utilized climate projections by the Community Climate System Model CCSM 4 and MIROC5 for the year 2050 and 2070 under RCPs 2.6, 6.0 and 8.5 emission scenarios. The highest percentage of areas having medium and marginally suitable climate conditions will decrease under RCP 2.6 by 2050 compared to the same level by 2070, since radiative forcing of RCP 2.6 peaks at 3 W/m^2in 2050 and returns to 2.6 W/m^2 by 2100 (Van Vuuren et al., 2007), the effect of RCP 2.6 will be less in 2070 than 2050 (Aduma et al., 2018). In contrast, a major expansion of areas of optimal suitability occurs under RCP 2.6 using MIROC5 in 2050 (Fig. 5), likely due to the variation in temperature and precipitation seasonality over the tea growing areas; hence, tea may be shifting from optimal to medium, marginal or unsuitable or vice versa, with the shifting of favorable precipitation and temperature conditions in the relevant area.

The precipitation seasonality (BIO15) (Fig. 4A) was found to be the most influential variable according to the results gained from the jackknife test. Evidently, a significant trend exists in the precipitation seasonality in Sri Lanka (Jayatillake et al., 2005). Previous studies also reported that high precipitation variability impacts tea quality and yields (Ahmed et al., 2014). According to MaxEnt modeling, with dynamic climate change, areas at higher and mid-elevations become more suitable than low elevation areas such as Galle and Matara for producing tea. Suitability for tea will move toward high and mid-elevations on the altitudinal gradient with climate change, whereas low-elevation areas will be the most reduced in suitability. The areas that in 2050 and 2070 will still be suitable for tea production are those main areas that are currently occupied with tea, particularly under optimum suitability class.

Looking into the specific suitability classes in 2070 (Fig. 6), a decrease in those areas that show “optimal” “medium” and “marginal” suitability are the most significant effect of climate change, with approximately 9%, 17% and 7.5% of the decline in the area from current to the future scenario of CCSM4 and MIROC5, respectively under the three RCPs. Considerable increases of optimal suitable areas are also noticeable under RCP 2.6 using MIROC5 in 2050, and a majority of these increases in these areas were found to be due to their conversion from “medium or marginal” categories into “optimal” suitable areas (Tables 7 and 8). By 2070, the southern parts of the country remain barely suitable for tea, but average suitability in Ratnapura increases. In business as usual scenario (RCP 8.5), the tea producing area further concentrates in the highly elevated areas of Badulla and Nuwara Eliya Districts. By 2070, the areas of optimal in Matara district may become marginally suitable, but for those in Nuwara Eliya District, suitability will still remain optimal or medium.

Regarding the results of the present model, *Camellia sinensis* shows a high probability within the lower range of the precipitation variation coefficient, and this variable has a major influence on the suitability habitats of *Camellia sinensis*. Notably, precipitation variations are lower in hilly areas than in the mid- and low-elevation areas in Sri Lanka (Wickramagamage, 2010); therefore, higher changes in suitability can be seen in low- and mid-elevation areas compared to the high-elevation areas according to the variations in seasonality of precipitation, which has the maximum influence on future suitability in the modeled scenarios (Table 9). According to the standardized precipitation index (SPI), areas in low-elevation areas will be more affected from drought than the areas in high- or mid-elevation areas (Eriyagama et al., 2009), suggesting that hilly areas will have a more favorable climate for tea cultivation. Considering all bioclimatic variables, precipitation seasonality was the most effective indicator for estimating the suitability of habitat for the species. In addition, based on the response curve for precipitation during the driest month (BIO14), the suitable precipitation in the driest month is greater than 30 mm, which confirmed that tea plants are particularly sensitive to water-deficit stress (De Costa et al., 2007).

Furthermore, the mean annual precipitation (BIO 12) makes a considerable contribution (11.3%) to the MaxEnt model. Generally, tea requires a fair amount of rainfall to sustain its life cycle and to produce high yield (De Costa et al., 2007). Precipitation rates in the future are projected to show strong diversification, and more repeated extreme weather, such as intense precipitation or droughts, are anticipated (Aheeyar, 2012; Singh et al., 2012; Yamane, 2009). Tea, which is a rainfed crop, is assumed to suffer considerably from the uncertainties in rainfall occurring as a result of climate change, especially in low-grown tea cultivations (Bandara, 2012). Therefore, water availability will play a critical role in sustaining future distribution of tea in Sri Lanka.

Furthermore, the distribution of rainfall has become exceedingly irregular in tea growing areas in Sri Lanka (Herath and Ratnayake, 2004). Tea grows well in hot-humid regions (Carr and Stephens, 1992), such as Nuwara Eliya, Sri Lanka, due to plentiful rainfall and sunshine. However, poorly distributed and low rainfall with high temperature has impacted tea production adversely, especially in the Matara, Galle, Monaragala and Kegalle districts. According to the Climate Change Knowledge Portal (2015), more precipitation will be received under the CCSM4 scenario than MIROC5 from 2020 to 2059, which is approximately 204.7 ± 6.59 mm and 103.9 ± 4.75 mm, respectively (See Table 4). This may be the reason that the overall future distribution of areas having medium and marginal climate suitability for tea in Sri Lanka is more affected by the MIROC5 scenario compared to the CCSM4 GCM in 2050, as the seasonality of precipitation had a high contribution to the model predictions. However, in 2070, the suitable climatic habitats for tea (i.e., optimal, medium) loss is greater under CCSM4 (Fig. 6). The average annual precipitation is expected to alter by 4%, with almost all models exhibiting a decline compared to historical records, with corresponding changes in the amount and spatial distribution of precipitation (Chandrapala, 1996). Regarding the IPCC (2013) projections, future precipitation events are ever-changing under Global Circulation Models, and extreme climate events across Sri Lanka will increase in the future. Future predictions stipulate that Sri Lanka will encounter a warmer climate and more intense precipitation, with the chance of a 10% upsurge in the length of both dry and wet seasons per annum in the main tea plantation areas (Wijeratne, 1996c). High-latitude terrestrial regions will experience strong precipitation events due to the additional water carrying capacity of the warmer troposphere. Many midaltitude and subtropical arid and semiarid regions are prone to have less precipitation (Stocker, 2013).

As elevation is highly related to temperature, the mean annual temperature also plays a considerable role in determining future habitats of tea plants with regard to suitability. Elevation may consequentially impact the distribution of tea by way of it having a direct relationship with the climatic conditions of a given location (Malbéteau et al., 2017). The areas having climate suitability for tea currently range from the elevation above 25 m up to 2500 m (Fig. 2). The areas in Sri Lanka at elevations below 393 m may experience the highest decline in climate suitability for tea, whereas the areas above 394 m may have the

highest surge in suitability in the years 2050 and 2070 (Figs. 5 and 6). The predicted probability distribution of tea in the future shows that the areas in Galle and Matara will reduce in suitability drastically across entire tea-growing regions. Tea habitats having optimal climate suitability may shift toward the high elevation areas in the future, whereas at lower altitudes, the areas are consistent with a warming climate (Revadekar et al., 2013) and are not preferred for the growth of tea plants. As a result of climate change, many species already have shifted their distributions to the higher latitudes and elevations, as reported in previous studies (Lenoir and Svenning, 2013; Perry et al., 2005).

According to previous field studies conducted by Wijeratne et al. (2007), shoot growth and tea yield at elevated temperatures, i.e., inside polytunnel (35.9 °C) in the low country region, (warmer region) were less than for that tea grown under ambient conditions (34.0 °C). The time taken for bud break was extended, and the shoot population density was reduced at elevated temperatures (Jayasinghe et al., 2018), conceivably showing the adverse impacts of global warming on tea production in the low country region.

Sri Lanka's long-term mean annual temperature in the lowlands is 27 °C, whereas it is 15 °C in the highlands. The mean temperature in Sri Lanka has already risen nearly 1 °C during the last century and continues to rise. According to the Climate Analysis Tool powered by the Nature Conservancy's Climate Wizard (http://ClimateWizard.org), the mean annual temperature under CCSM4 scenario will range from 27.2 °C to 28.3 °C from the year 2020 to 2079, while it will be 28.2 °C–28.6 °C under MIROC5 scenario for the abovementioned years. While incremental temperature increases help areas in high- and mid-elevation areas reach the optimum temperature range for tea cultivation, tea growing areas would be extended, approaching important ecosystems in hilly areas. This might be beneficial for tea production in regions with relatively cold climates, such as highland areas such as Nuwara Eliya, but this would have a negative effect as warmer and humid weather attracts pests to places where they were earlier controlled by the cool mountain weather, and diseases would be more widespread during heavy rains. Thus, the areas in the highlands may also eventually lose their benefits if warming continues. Therefore, those growing regions that are currently well known may become unsuitable for tea cultivation in the future.

Tea also prefers areas with the mean annual temperature range of 14–27 °C (Fig. 4B). The highest probability of *Camellia sinensis* occurrence was related to areas having a mean annual temperature of approximately 20 °C. The resulting response curve better matches the tea growth condition, as previous studies indicated the optimum temperature for shoot growth of tea is in the range of 20–30 °C (Carr, 1972; Carr and Stephens, 1992; Jayasinghe et al., 2018; Smith et al., 1993; Tanton, 1982), and this value for Sri Lankan tea cultivars is 22 °C (Mksld et al., 1999; Mohotti and Lawlor, 2002; Wijeratne, 1996a). Of the seven predictor variables used to build our model, annual mean temperature (BIO1) and mean diurnal range in temperature (BIO2) emerged as the strongest range predictors after BIO15, highlighting that these variables were important interpreters of suitable habitat because of the potential impact of temperature on tea physiology and survival (Mohotti and Lawlor, 2002).

Tea habitats are more unlikely to exist in areas with monthly extreme diurnal variation in temperature, which is below 50 and above 95 (See Fig. 4D). In general, the photosynthetic capacity of tea is negatively affected by high and low diurnal temperatures, which alter leaf temperature, shoot growth and stomatal conductance (Mohotti and Lawlor, 2002), and may be responsible for responses to mean diurnal range. Nuwara Eliya demonstrates the highest diurnal temperature change trend in all seasons, with the highest (-2.37 °C) occurring in the Northeast monsoon season (Jayasundara and Kasthuri, 2016; Sujeewa, 2011). The higher rate of diurnal temperature change in Nuwara Eliya provides evidence for the incidence in changing suitability habitat for tea under different GCMs in future climate. According to the study conducted by Sujeewa (2011), little changes in temperature occurred at Ratnapura during the years from 1871 to 2010, as this area is located more than 60 km away from the sea and is near the base of the central hills. Therefore, given this locale, sea and land breezes have little influence on weather and climate variables at Ratnapura, which reasonably explains our model as the higher rate of incremental changes in habitat suitability are indicated for tea from future climate change too (Figs. 5 and 6). The most uneven change in temperature was observed in the coastal areas due to the effects of the sea breeze. Differences of mean diurnal range, normal annual, seasonal, monthly and daily minimum and maximum temperature from reference minimum and maximum temperature values have resulted in significant warming trends in the districts of Galle and Matara (Sujeewa, 2011). This trend of temperature variation might lead to absences of optimal and medium climate suitability habitats for tea in Galle and Matara districts (Figs. 5 and 6).

Changes in climate suitability for tea have been recorded in other tea producing countries. Malawian scientists also identified suitable tea growing areas in Malawi under climate change scenarios for the periods 2020–2049 and 2040–2069 in RCP emission scenarios for 19 GCMs (Bartling et al., 2017). The models projected an overall loss of suitable areas for tea production of Malawi in the future. Modeling results have also shown a severe change in the suitability of tea growth in Assam in 2050 and 2070 (Bhagat et al., 2016). According to the future climate projections in China, the main tea producing area could gradually shift from south to north (Brouder and Eriksson, 2013). In Kenya, the optimum tea-producing zone is expected to shift to a higher altitude of between 2000 and 2300 m by 2050, compared with the current altitude of between 1500 and 2100 m, and suitable areas for tea growing is projected to be reduced by 22.5% by 2075 (Leshamta, 2017). In Uganda, suitable areas will shift up the altitudinal gradient, whereas the suitable area for tea will decrease to between 20 and 40%, compared with the current suitability of 60–80% (Muthee et al., 2019). In Eastern Africa, up to a 40% yield reduction is estimated due to the diminutions in suitable areas caused by temperature increases (Adhikari et al., 2015).

Our model also predicts that tea will hardly be found in other areas where tea had not previously existed. The suitability map indicates that the prospective habitats in the southern inland areas are diminishing across the study area, and this could cause an acute risk to the long-term development of the tea sector. This region currently contributes 60% of the total tea production in Sri Lanka (Bandara, 2012). The high potential suitable habitation patches increase along and outside of the Kandy-Matale boundary, particularly in the Matale and Galle district (Figs. 5 and 6). An area of 11,816 km^2 is projected as the potential area of having high climate suitability (i.e., optimal or medium) for tea relevant to the current time. However, the actual total extent of area under tea cultivation has been calculated at approximately 2220 km^2 (Bandara, 2012), indicating the potential for expanding tea cultivation to other possible areas in Sri Lanka. Additionally, this is an indicator that the tea cultivation can be introduced to new areas. Knowledge of the climate suitability for tea (i.e., current and future) and land use patterns are crucial to expand or establish new tea cultivations. Notably, this research only looked at climate suitability for tea; the actual suitable areas available in the future will be lower due to the impact of other factors such as land use and soil suitability.

5. Conclusion

One of the main premises of the climate suitability studies is that this approach can help to determine the areas having climate suitability for the future distribution of species. The comparison of the current and future distributions of suitable tea growing areas revealed a decline of approximately 10.5%, 17% and 8% in the total area for "optimal," "medium," and "marginal" suitability between current and future scenarios. These projections indicate that by the years 2050 and 2070, climate would have a negative effect on habitat suitability of tea in Sri

Lanka. Based on the environmental and climatic parameters used in this research, tea cultivation may shift, such that tea may or may not grow in some of the areas where it is currently grown if no suitable adaptation measures are implemented. This study has yielded useful information for prospective stakeholders in the tea sector for making tea production system more climate-resilient and identifies areas having a potential for establishing new tea plantations in Sri Lanka. Further improvements to the model could be done with presence-absence data; topographic data; existing land uses; land cover in the suitable areas; socioeconomic conditions; adaptation techniques currently used by tea growers; and other important bioclimatic variables such as humidity, solar radiation, light intensity, soil properties and clonal characteristics for better assessment of climate suitability for tea plant.

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